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**Digital Twin Application for Smart
Product Management and Production
Engineering and Deployment in China**



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Bewegung*



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Abstract

New technologies are enablers for competitive advantages. The digital twin is a revolutionary technology and is supposed to be such an enabler.

The object of this paper is to figure out the possible application fields of the digital twin and to qualify the advantages and potential savings related to these applications. In this paper the digital twin is presented in different kinds as a means to optimize the value chain. It is demonstrated how the concept of the digital twin can be integrated into the entire process of innovation and technical product management including artificial intelligence. Examples from China show how to gain competitive advantages.

Key Words:

Digital twin, artificial intelligence, application fields, value chain, engineering, technology



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数字孪生在中国智慧产品管理和生产设计制造中的应用

摘要

新技术可以帮助企业从竞争中脱颖而出。数字孪生是一项革命性的技术，有望助力企业成功。本文的目的是找出数字孪生的潜在应用领域，明确该应用的优势和潜在的成本。本文研究了不同类型的数字孪生技术，以对价值链进行优化。本文通过中国某公司的实例，展示了如何将数字孪生技术融入创新和包括人工智能在内的技术产品管理，以获得竞争优势的整个过程。

关键词:

数字孪生, 人工智能, 价值链, 工程, 技术

Digital Twin Application for Smart Product Management and Production Engineering and Deployment in China

von Günter Hofbauer¹, Zhang Ting², Daniel Maier³ and Li Zhi⁴

1 Introduction

The digitalization implicates the evolution and rapid progress of new generation technologies. These technologies provide a wide range of new and smart applications. Especially robotics, big data, cloud computing, internet of things and artificial intelligence are driving industry towards industry 4.0 in terms of smart implementation and exercise. The power of smart industry opens manifold benefits for companies to establish competitive advantage and to achieve value added. Activities can be executed better, faster and cheaper. Especially the performance of the product life cycle management seems to be qualified for the application. Beyond the above mentioned new technologies, there are further applications arising. Figure 1 shows the results of a survey among executive officers in the German Manufacturing Systems Engineering industry, answering the question which technologies have the highest probability of transforming their industry (PriceWaterhouseCoopers 2021). Figure 1 shows that the concept of digital twins is an upcoming technology, amongst others like artificial intelligence, virtual and augmented reality, blockchain and drones. This is a strong indicator that digital twins are already considered to be helpful in the digital transition. Even the technological research and consulting firm Gartner describes the digital twin as an emerging technology and predicts an estimated revenue of \$183 billion for the overall digital twin market by 2031 (Gartner 2022a). This tremendous potential is a well based justification to have a close look on the potentials of the concept of digital twins.

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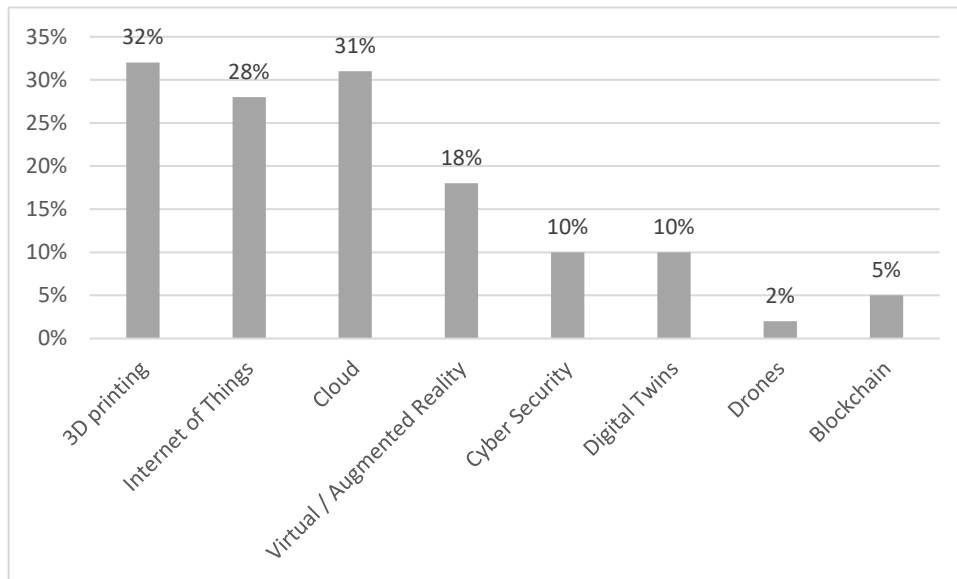


Fig. 1 Most promising technologies (PWC 2021) (own graph)

This article presents the digital transformation of the value chain and depicts how to integrate the concept of the digital twin into product lifecycle management. As it is a new and promising technology, many companies quest for applications of this new approach.

Firstly, the concept of this revolutionary technology will be explained in general and will be introduced from different perspectives. Different types of digital twins will be presented.

Secondly, the digital twin concept will be applied to the value chain in terms of product lifecycle management. In this context a comprehensive framework will be elaborated to show the application possibilities along the product lifecycle. Thirdly the benefits of using digital twins will be specified for each phase of the value chain.

The contributed value of this paper is the presentation of a comprehensive description of the impact of the digital twin in application to the value chain. The benefits of applying the digital twin will be pointed out for each phase in value creation. These benefits may become ambition for industrial implementation and topic of academic discussion as well.

2 Initial situation

In nowadays widely spread approaches to create value in industry there are many problems, which can be identified related to time, cost and quality. On the other side it can be stated that new technologies are introduced to overcome traditional problems. Especially big data driven technologies are emerging. The big obstacle of using big data in an integrated way is that most of the research is focused on physical products rather than virtual objects. Additionally, the essential data are not available due to the missing communicative link between physical product and virtual model or the data over the different phases over the lifecycle are not integrated. This means that the data flow is interrupted, the data are segregated, uncomplete and incompatible and not useful to optimize the entire value chain. These problems imply suboptimal results in PLM in terms of less intelligence, less efficiency and less synergies (Tao et al, 2018, p. 3563).

Hence the basic hypothesis of this paper can be formulated that the whole potential of digital transition is not fully exploited yet. The question of research is how the concept of the digital twin can be utilized to take advantage of that potential.

The basic weakness in most of the industrial value chains is twofold: Firstly there are not sufficiently integrated activities and secondly relevant information is missing or cannot be used for optimization due to lack of compatibility.

The integration can be accomplished by installing clearly defined value creating processes without breaking points (Hofbauer/Sangl 2018, pp. 309-321). The advantages can obviously be derived. The most important are:

- overall responsibility throughout the entire process
- concentration on value creating activities as a whole
- reduction of mutual dependencies, interfaces and fractures

The second aspect of missing information can be provided through big data, cloud computing and artificial intelligence. In order to use big data, it is important to get the relevant information to the right place in the right time. The digital transformation needs extensive data collection of defined processes within their specific context. A failure detection has to assure that only data sets without faults will be used (Qi/Tao 2018). Once there is a valid set of data, this

platform serves as an information desk. Information is available about past and current conditions. This platform is the basis for the projection of future situations.

From figure 2 (PWC 2022, Digital Factory Transformation Survey 2022) can be derived that all promising applications, which are already implemented, piloted or planned, are driven by data-enabled optimization. A second finding is that different types of digital twins are mentioned, referring to the product lifecycle or the mirroring of the overall factory.

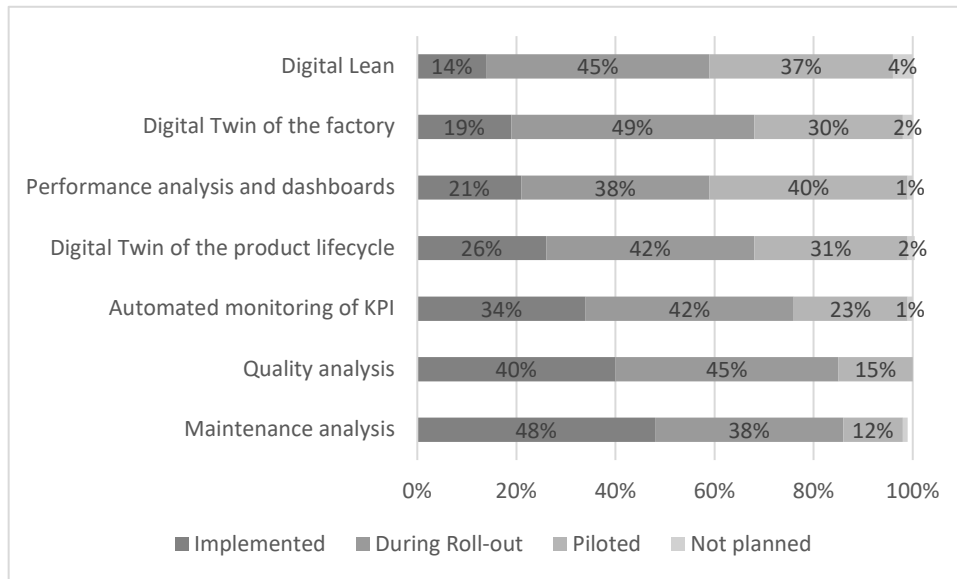


Fig. 2 Application of big data analytic technologies and their implementation status (PWC 2022)

3 Literature research and solution statement

The term digital transformation contains a wide variety of meanings and definitions. Frequently it is put on a level with digitalization. The analysis of the versatile definitions in literature leads to identify specific issues for this publication. The digital transformation indicates the integration of technological developments of the digitalization into different areas of companies. In doing so business processes and total value chains can be optimized on the basis of collected and utilized data. Further on company departments and divisions as well as customers and other stakeholders can be networked. Thus the digital transformation refers to business activities. The digitalization in general also includes the impact on society and environment.

The digitalization currently drives the implementation of virtual product models particularly in development and manufacturing, but mostly on a stand-alone basis and not related to each other. Coming from this perspective it is necessary to bridge the gap between the different steps. Once a virtual twin exists, the use may be extended throughout the whole value chain.

In this chapter a specific look on business activities related to the PLM and production engineering will be given. In chapter 4 the potential of the utilization of the digital twin will be highlighted for different process steps of the PLM including production engineering.

3.1 Product Lifecycle Management (PLM)

Managing a product all over the lifetime is a business activity to create value. This activity is called PLM and takes care about the product from the very first idea through the whole life of a product until it disappears from the market (Hofbauer/Sangl 2018). The PLM has to be executed in the most effective and efficient way to create competitive advantage and to earn profits. Therefore tailored innovations have to be introduced to the markets. To gain competitive advantage companies have to execute all related activities in a better, faster and cheaper way than competitors. The integration of all those activities in an interrelated process is essential to mine synergies.

The PLM covers all required value-creating activities of a product from the beginning to the end of a product life cycle. According to a well-proven model, four process steps can be displayed in brief (Hofbauer/Sangl 2018, p. 341).



Fig. 3 Four-step PLM process model [own work]

Figure 3 displays the consolidated process phases of the PLM. This process consists of four phases, which will be analyzed in terms of applicability and benefits of digital twins.

3.2 Digital Twin

The concept of the digital twin was presented the first time by Grieves at the University of Michigan (Grieves 2014). As displayed in figures 1 and 2 the digital twin is among the most promising technologies for the near future. Due to the enormous potential of smart applications in industry 4.0, the concept of digital twins is encouraging for industry. Some companies like Siemens, General Electric, Dassault, etc. already use the digital twin in their operations, mostly for manufacturing practice.

Because of the emerging implementation, some definitions and explanations were proposed. The most common aggregate definition of the digital twin is consisting of three components: physical product, virtual product and the connection in terms of communication between them (Glaessegen and Stargel 2012).

The digital twin is a virtual image of the physical object, they are linked and able to communicate among each other (figure 4). The objects may be complete units, single parts or components as well as processes or even entire production facilities (Grieves 2018, p. 67; Schonschek 2018, p. 42).

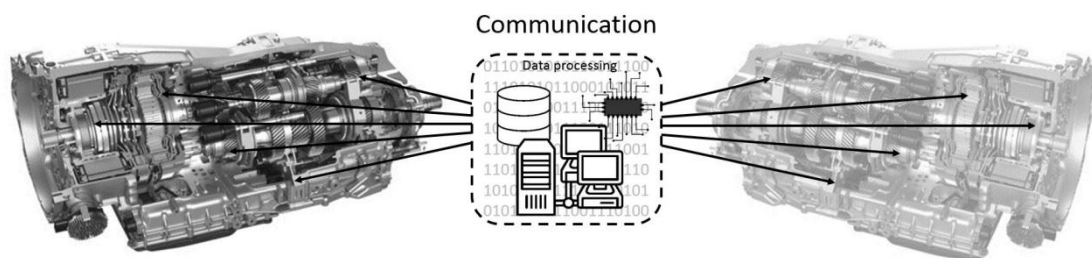


Fig. 4 Demonstration of physical and virtual twin of an automatic gear box
(by courtesy of © ZF Friedrichshafen AG)

The two-way dynamic mapping of virtual models and physical objects of digital twins facilitate the integration into the product lifecycle management (PLM) throughout the whole value chain. Especially in today's highly competitive markets the effort to shorten the time to market, increase cost savings and enhance the product development performance push the implementation of virtual product models. The efficiency and effectivity can be increased from product design, production planning to manufacturing implementation towards utilization and finally to maintenance, repair and overhaul (MRO).

In principle the idea of the digital twin is not new, because since computer-aided design (CAD) was used, there was a digital representation of a physical object. But nowadays capabilities to handle big data in terms of data collection, data mining, data analysis and prediction offer a huge potential to combine real world with virtual world (Qi/Tao 2018). The digital twin is to create virtual models for physical objects in the digital way to simulate the behaviors. So it can be stated that the combination of new technologies fosters the capability of digital twins. The advantages are summarized as follows (Gartner 2022b):

- The robustness of the interaction of real and cyber-physical objects is increasing and strongly supports the monitoring of specific applications
- Especially the feedback to the real world can be used for optimization of processes and operation in real time
- The interaction between the two worlds can be used to evaluate scenarios and predict future behavior for reliability and maintenance
- The utilization of big data in combination with artificial intelligence (AI) is useful to create new applications in enterprise decision making

The digital twin of a real object is a set of digital information that completely specifies and characterizes a potential or real-existing product in all dimensions. In the best-case scenario any information available from monitoring a real object can also be received from the corresponding digital twin.

The three main types of digital twins can be characterized (Grieves 2018, p. 68): Digital Twin Prototype (DTP), Digital Twin Instance (DTI) and Digital Twin Aggregate (DTA).

The DTP describes the real product in the early stage of prototyping. This type comprises all necessary information, which is necessary to specify and create the physical version. The specific feature is, that the virtual twin is created before there is a real product. Usually the virtual twin is the twin of an already existing product. The specific advantage is that the DTP can be tested before a physical version is produced.

The second type is called Digital Twin Instance (DTI). The DTI is related to a defined corresponding real-existing product and mirrors that physical object throughout the whole lifecycle in all circumstances. Depending on the requirements data from the twin may disclose information about operation grade, process parameters, workload, reliability, construction dimensions, abrasion, attrition, service information, part changes and MRO.

The third type of Digital Twin is considered as Digital Twin Aggregate (DTA). The DTA is the aggregation of all related corresponding DTIs. This means that the DTA is not related to one twin and is not mirroring one specific physical twin. Rather than that the DTA has access to all DTIs and collects data from all of them on a continuous basis or just on demand. This kind of digital twin helps to base the statistical data on a broader foundation to get more reliable data than just from one source.

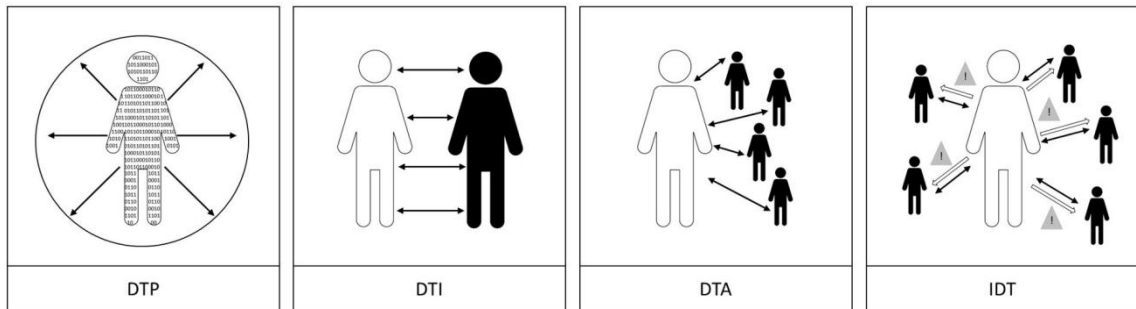


Fig. 5 Different kinds of Digital Twins (own work)

Besides the aforementioned main types of digital twins there is another type, which is related with artificial intelligence (AI). This type is called Intelligent Digital Twin (IDT). The common conception is that the digital twin is a passive storage of data from the physical object, which can be canvassed about specific issues or behavior in order to get tailored information about the investigated topic. The IDT however is considered as a proactive and intelligent one, which actively presents relevant information and predictions based on the contextual indication of the physical object depending on the environmental status. Thus failures can be avoided and the entire life cycle can be simulated (Tao et al., 2018, S. 3564-3567) under various conditions.

Figure 6 shows the range of impact over the value chain of the different kinds of digital twins.



Fig. 6 Range of impact of different digital twin concepts (own work)

The major uses of digital twins can be stated as interrogative and predictive (Grieves 2018, p. 69). Interrogative means that the digital twin can be asked about past and current conditions,

failures and histories. Though it does not matter, where the corresponding physical twin is located in the world. The predictive use means that the digital twin can provide information to predict the performance, future behavior, consumption data, failures and required maintenance and spare parts.

The crucial issue is data collection and processing, which enable the generation of the virtual and cyber-physical objects as twins. The evolution in sensor, processor and microchip technology as well as computing power enables the way towards highly sophisticated data management. Sensing routines combined with communication capabilities assure that the virtual twins are fed with the required reliable data. Procedures like data mining, deep learning, pattern recognition and others make use of these data in order to detect correlations, dependencies and deficiencies.

A definition at great length was provided by NASA in the company's integrated technology roadmap (Glaessgen/Stargel 2012): "A Digital Twin is an integrated multiphysics, multiscale, probabilistic simulation of an as-built vehicle or system that uses the best available physical models, sensor updates, fleet history, etc., to mirror the life of its corresponding flying twin."

3.3 Artificial Intelligence (AI) as a prerequisite for the IDT

3.3.1 Understanding and institutional utilization of AI

In order to be capable of handling big data and tremendous amounts of generated data, which are on the one hand side requirement on the other hand side results of the application of digital twins, new approaches and methods of data analysis are indispensable. Particularly with regard to IDT, it is necessary that the digital counterparts of physical objects, regardless of their stage of development and number, can make predictions and proactively offer solutions, for example to identify sources of failures and to eliminate them before occurrence. The underlying digital technology for this is AI, which is currently massively in public awareness and interest. The term was first mentioned at the Dartmouth Summer Research Project on Artificial Intelligence (DSRPAI) hosted by John McCarthy and Marvin Minsky in 1956. The aim of this conference was to define a general research agenda for intelligent machines/computer systems, with the result being rather the foundation stone for scientific AI research of the following decades (Haenlein/Kaplan 2019).

In general, AI is a term that describes the general intelligence of non-human systems. The term defines the ability of computer systems to independently collect and analyze data and to

find solutions in complex situations using rational decision-making (Akter 2022). The characteristic component of this poses the independence of the system, which does not rely on behavioral guidelines predefined by human software developers, but rather makes decisions independently based on available data and the nature of the problem and situation. This independence from human intervention is the distinctive feature of the technology. Other terms that are often used analogously in the literature are machine learning (ML) and deep learning (DL). ML is less a variation of AI, but more of a requirement. ML describes the learning ability of systems to examine connections and to recognize patterns from huge, often completely unstructured amounts of data (Akter 2022). A practical example would be Netflix's recommendation mechanism, which stringently adapts the program offered based on the consumer's previous search and usage behavior.

DL, on the other hand, describes the most recent development of AI: the attempt to simulate human neural networks. This would mean a technological upheaval, as the performance of the human brain has been considered superior for a long period of time and could not be artificially imitated for decades. Nevertheless, there are already areas of application in which DL systems are used, despite of being very limited to specific tasks and areas. For example, predictions on the stock market, prediction of customer churn rates or examining the creditworthiness of private customers can be listed here (Bruyn 2020).

Even though various terms exist, which describe upstream or downstream stages of AI or variations in specific application areas leading to various different definitions, there are single components that are commonly viewed by scientific research as distinctive features of AI:

- Independence from human intervention
- Ability to rational decision making
- Self-Learning mechanisms
- Data as the main prerequisite (big data)
- Touchpoints to non-digital environment
- Ability to process natural language (Akter 2022)

A mistake often made in this context is to consider AI as a single technology. Rather, AI is a consortium of many different individual technologies, which, in their interplay and interaction with the environment, determine the ongoing development of novel, intelligent digital solutions (Berente et al. 2021). The progress made by this digital technology is therefore less due to the growing spread and use of AI as a whole, but rather due to the evolutionary

developments of the individual technologies involved. Examples of this include pattern recognition, speech processing and generation of content, like by the applications DeepL or ChatGPT.

While the last two software solutions mentioned are primarily used by private individuals, companies have also already recognized the potential of AI and are making investments and implementation attempts. This becomes particularly obvious by considering the development of the market for AI applications. While the market volume was around 100 million USD in 2021, the market volume will progressively increase to a value of 2,000 million USD by 2030. This represents an increase of almost 2,000%. Figure 7 shows the development of the AI-market size with a forecast included for 2023.

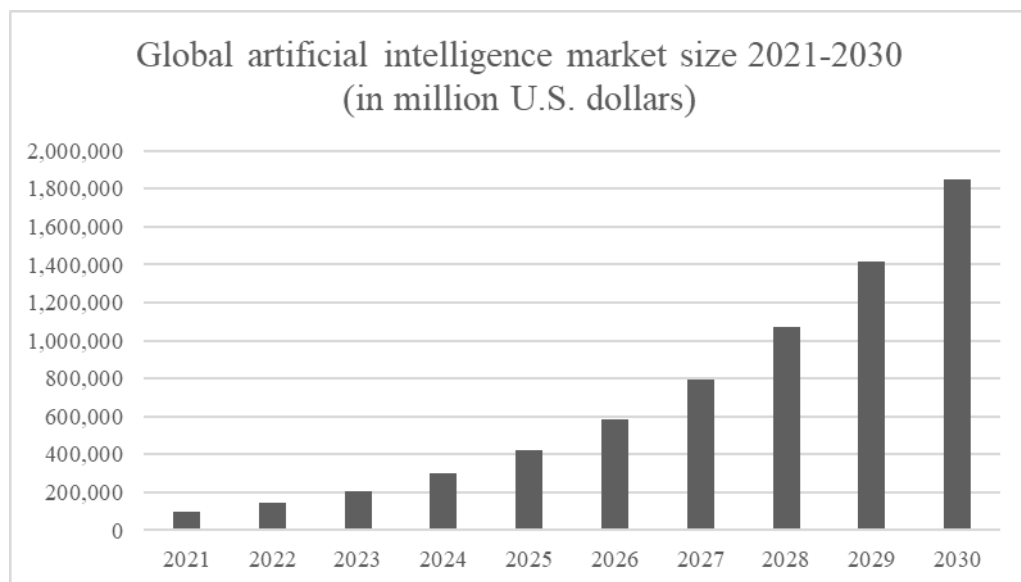


Fig. 7 Artificial intelligence (AI) market size worldwide in 2021 with a forecast until 2030 (in million U.S. dollars)
(Next Move Strategy Consulting 2023)

As the diagram shows, AI poses an emerging technology consortium with enormous potential and the companies are heavily investing in accordance to the expected added value for the organization.

The extent of the diffusion of AI in private companies depends largely on the industry/economic sector and the internal application area. While the adoption of AI is already quite advanced in service-oriented and technology-intensive industries, there are business sectors where it is still in its early development and acceptance stages. In particular, very sensitive functions such as human resources or corporate finance should be mentioned here.

Despite of this, AI is already noticeably widespread in services, marketing & sales and product development (Stanford University 2022).

Particularly in the finance sector as part of customer services, an adoption rate of 40% is already achieved, which corresponds to the application in the automated creditworthiness check mentioned above. Regardless of the sector and area of application, in a study conducted by McKinsey & Company, 34% of the respondents stated that AI is already in use in their company (Stanford University 2022).

Figure 8 shows the results of the study for the respective industries and company functions.

AI adoption by industries and functions worldwide 2021	Tech/ Telecom	Automotive & Assembly	Business, legal and professional services	Financial Services	Health/ Pharma/ Medical	Consumer/ Trade	Total
Human Resources	9%	11%	14%	10%	9%	2%	9%
Production	12%	26%	8%	4%	11%	18%	12%
Marketing & Sales	20%	20%	28%	24%	14%	22%	20%
Product / service development	23%	15%	15%	20%	29%	17%	23%
Risk Management	13%	4%	13%	32%	13%	1%	13%
Services	25%	18%	26%	40%	17%	15%	25%
Strategie & Corporate Finance	9%	6%	8%	13%	12%	4%	9%
Supply Chain Management	13%	17%	13%	8%	9%	18%	13%

Fig. 8 AI adoption by industries and functions worldwide 2021 (Stanford University 2022)

In addition to the specific areas of application, the approach in which the technologies are used in the organizations must also be taken into account. Enholm, Papagiannidis, Mikalef, and Krogstie have identified two possibilities in this context: Automation and Augmentation (2022).

Automation means that a task that was previously carried out by humans is completely and holistically taken over by the technology, making the human contribution obsolete (Enholm et al. 2022). This is applied primarily in the optimization of repetitive standard processes. The concrete advantages of this automation are an increased efficiency and thus lower costs as well as a better usage of human labor for meaningful and value-generating activities.

Augmentation, on the other hand, means that the responsible main actor of the task is still an employee, but he is supported by digital technology to achieve better results. The focus of these efforts is on expanding human performance and not on replacing it (Enholm et al. 2022).

In this context, concrete application examples can already be found in medicine. For example, image recognition can support the analysis of X-ray images and detect cancerous growths at an early stage, even if they are still microscopic and would not be observable by eye (Enholm et al. 2022).

It can therefore be stated that the use of AI is generally increasing rapidly, which heavily depends on the industry and the company function. In addition, a distinction must be made whether the technologies are used as replacement or extension.

3.3.2 AI and digital twins

Specifically, in the area of intelligent digital twins AI poses an inalienable technology. While the digital twin itself in form of DTP, DTI or DTA primarily shows a description / reflection of the current situation and status of physical objects, only the combination with a form of intelligence constitutes the possibilities of utilizing this information for improvement and ongoing optimization.

In former times, this was done by analysts and engineers, who have a deep understanding of the physical instances and, due to their experience, are capable of making predictions based on the generated data. A negative effect of this procedure is the fact, that these resources are occupied with these non-value generating activities and cannot use their time effectively, for example for the development of new products or services or for the streamlining of the production processes.

The combination of the digital twin with AI eliminates this time-consuming activity as the diagnosis and predictions are automated providing time reliefs for the engineers and analysts. Thus, the reduction of human intervention and the increase of machine enabled automations can be observed as the main benefits of the IDT. In concrete, AI is conducting the following tasks based on the information gained from the virtual interface:

- Diagnostic – Identifying the origins of failures and inefficiencies
- Prediction – Forecasting of potential future events
- Prescriptions – Giving options of intervention (Agrawal et al. 2022)

It can be observed that in this approach AI functions merely as automation according to the classification of Enholm et al. mentioned above (2022).

Apart from this very restrictive point of view, reducing the human participation to an absolute minimum, there are currently also collaborative opinions towards the application of AI in digital twins. These perspectives place significantly more value on the human component which remains as the decision maker and responsible part. Such intelligent decision-support systems utilize the analytic power of AI to collect, analyze and create reactive and proactive options of action for providing a limited amount of choices to the decision makers (Ivanov 2023).

Key mechanism to achieve this is the continuous simulation of all processes and status of the physical entities and the application of feedback-loops from the digital twin to the AI and vice versa. This ongoing self-learning enables the digital twin to increasingly create a picture which more and more corresponds to the practical environment and enables machine learning for an improvement of diagnostics and predictions. Requirements for this are an availability and monitoring of all data in real-time (Ivanov 2023).

In business practice especially these two factors pose a main hurdle for the implementation of the AI-supported digital twin. While in a purely digital world unlimited data availability can be achieved quite easily, physical entities normally do not provide the data automatically. Instead of, the information has to be included manually.

With regard to the digital twin this poses a major problem as delays and inefficiencies are unavoidable by this method of data generation.

To overcome this obstacle, an increasing number of sensor technologies are used in the production plants to enable physical objects to simultaneously transmit all generated information. Examples for this are vision sensors allowing the detection of objects and the recognition of images as well as voice sensors in form of voice assistants or triboelectric auditory sensors, which are capable of recognizing sounds within a broadband of 100 Hz and 5 kHz (Zhang et al. 2022).

Another extensively used sensor technology is the application of tactile sensors. These sensors react to physical interaction and skin touch enabling an interface between actions done by machines and production workers (Zhang et al. 2022). Furthermore, a sophisticated variation of this approach is the usage of data gloves, tracking all movement and actions of the wearer (Zhang et al. 2022).

By utilizing these technologies, the data can be generated and processed in real time while the manual input of information gets obsolete. This can be seen as the prerequisite for the AI implementation in the digital twin.

After machine learning, intelligent diagnosis and decision making is activated in the system, a variety of benefits can occur, enabled by the novel automated intelligence in the physical-digital-system:

- Reducing downtime of machines / production plants
- Enhancing process stability
- Eliminating anomalies
- Increasing performance
- Reducing losses / waste (Kharchenko et al. 2020)

Which of these advantages can be achieved is totally dependent on the availability of technological solutions and the extent of adaption in the single processes. For small-and-medium-sized companies (SMEs) there are already standard solutions for their digital twins, which can easily be connected and provide a solid starting point for system-based decision making in physical-virtual systems (Kharchenko et al. 2020). These solutions can simply be purchased by specialized vendors, such as Amazon Web Services as a well-known example. Regarding the adaption of AI and digital twins in the processes, the acceptance of the single employees plays a critical part. Here change management methods and extensive trainings for sensitization can make an impact. In order to unlock the potentials of AI-digital twin combinations all members of the organization have to be fully convinced about the technology.

4 Impact on PLM and production engineering

The examination of the impact of digital twins will be represented by the means of the short version of a product management cycle. The most important phases for the use of digital twins are design, operation, use and service. The concept of the digital twin however is not considered as an entire model of the physical product, in fact it is a set of corresponding

operation data and simulation models, which are sufficient and appropriate to mirror the behavior of the real twin (Boschert/Rosen 2016).

By means of the digital twin it is possible to check in advance all requirements throughout the whole product lifecycle in terms of cost, design, manufacturing capability, logistics and execute simulations through the expected useful life until the recycling requirements in the service phase. This procedure has the tremendous advantage that real physical products will only be released for realization, if all relevant and determining requirements are fulfilled. Thus it is feasible to avoid mistakes, failures and flops and simultaneously save time and money. In summary it can be argued that the DTP enables to overcome inherent problems of nowadays PLM and leads towards effectivity and efficiency. Competitive advantage is strengthened by shortening time to market, lower investment and lower expenses, higher quality and higher margins.

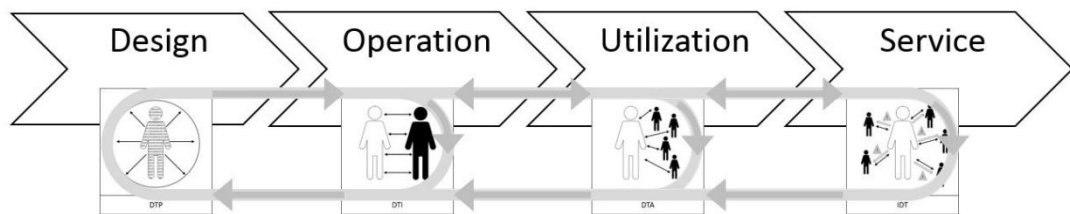


Fig. 9 Phases of PLM linked with different kinds of the digital twin (own work)

The phases shown in figure 9 contain a set of different activities respectively. These activities will be reviewed with regard to value creating potentials.

4.1 Design

This first step of design and engineering provides real benefit to PLM through the application of a digital twin. In this phase the concept and technical product are going to be developed and the basis for the engineering is initiated. Feasibility studies and product tests have to be executed, before real prototypes are engineered and physically built. The utilization of the digital twin should be executed from the very first beginning of designing a product, because the collected data build up the data basis of this object in subsequent steps of development (Schleich et al. 2017, pp. 141-144) and engineering.

In this early phase the Digital Twin Prototype (DTP) is relevant and beneficial, because there is no real product existing yet and is not necessary either. The virtual model helps to improve the geometrical shape as well as the functionality of the sequent physical product. This virtual model will be filled with engineering and design data, operation modes and mechanisms. This early data set enables to check the first functionalities and the master plan. The character of this kind of digital twin is responsive.

As soon as there is positive response out of the development stage, the next step is initiated and the detailed product concept will be developed. Also for this part data from previous product developments are relevant to complete the DTP quickly. In case that there is positive response again out of this step referring to the whole mode of operation and functionality, the next step can be initiated towards establishing the virtual twin. With increasing data volume the virtual twin becomes more concrete.

As soon as the product concept is accomplished, the digital twin can be applied to do the testing. Thus different product concepts can be put to test and simulation without the necessity of having a real prototype (Maplesoft 2018). Thus predictions of performance and of failure can be undertaken without spending money on building a physical prototype. Not before the virtual twin is faultless and optimized, the prototype can be constructed. There are additional benefits in prototyping, because also virtual prototypes can be used as destruction product as well as to examine performance and weak points.

Virtual prototypes are required for rapid prototyping. Powerful IT-systems and additive manufacturing processes enable shorter production time for physical prototypes. All relevant manufacturing data are already included. Different types and versions can be analyzed and simulated till an optimized option is achieved. Predictions about the performance of the final product are possible on that basis (Schleich et al. 2017, p. 144).

Subsequently the virtual twin will be complemented with the physical twin. Since all this work can be done before investing in a real prototype in the very early stage, a high potential of possible savings in time and money can be realized. Thus the required time for development is shortened and the risk of construction faults is eliminated as far as possible.

So the preparation of the PLM for the next phase is done in the best way and this first phase ends up with the completion of the development of the product and design freeze. This is the basis for real prototyping and subsequent final products. The potential to decrease time to

market is estimated about 50 percent by using virtual twins in product development (WiGim 2017).

4.2 Operations

As soon as there is a physical prototype of the product in addition to the virtual twin and both are able to communicate with each other, the digital twin instance (DTI) may be created. Now it is possible to combine the digital representation to the real-existing artefact: the product, the equipment and production line and even of the whole plant infrastructure. Thus it is feasible to move the virtual twin through the whole engineering and operation process and this process can be virtually tested and optimized. The generated data set has to be intermateable to be used throughout the whole PLM. Especially in the phase of operations the steps production planning, production engineering and manufacturing implementation can be tested and optimized before any physical investment has been done or any physical work has been started. The benefit will be more reasonable manufacturing planning, precise production control and higher efficiency towards smart manufacturing (Klostermeier et. al. 2018, p. 300). The manufacturing operations are responsible to assemble the parts, components and sub-systems into products according to specifications to be applied. In the next step the products are subject to quality testing and final inspection. The advantage of using digital twins is that all these routines can be verified and optimized, before the equipment is installed. The only prerequisite is that the digital twin of the product with all its parts and functions is able to communicate with the digital twins of the manufacturing and testing equipment. All specifications, characteristics, process parameters, conditions, production terms and other factors of influence can be recorded in real-time for monitoring and optimization of the entire manufacturing process (Tao et al. 2018, p. 3564). The digital twin does not only serve as a representative of the physical product and its current status, furthermore it is supposed to serve for predictions about operating parameters and expected handling behavior. In addition to the application of the digital twin for specific production lines it is possible to combine all production lines and related activities to get a virtual reproduction of the entire factory. The complexity of a product or a production line or even a plant infrastructure boosts the volume and type of information, which is needed to create a corresponding twin. This digital aggregation results in a smart factory (Daimler 2018), which is a completely digitalized

twin of the entity of real processes. These processes like flow of material, production process, in-plant logistics may be combined and optimized in the aggregate of the whole enterprise (Fraunhofer 2017). This is an important supporting function of the virtual twin to calculate dynamic lot sizes, allocation of resources, arrangement of equipment, supply of parts and so on to produce at optimal cost (Tao et al. 2018, p. 3569).

Therefore it is important to get the right data and let the twins communicate to each other. The prerequisites are sensor controlled data collection on the one hand and connectivity on the other hand. In this way parts, products and production processes can be monitored and defective items and inefficient processes can be detected easily.

By entering the build phase of manufacturing the digital twin facilitates to manufacture the product first digitally and make it as lean as possible before the equipment is installed and budget is spent.

4.3 Utilization

In this phase of the product lifecycle the real product has to be bought by the customer, before the product can be used. Prior to this the product has to be communicated, demonstrated and sold by the vendor (Hofbauer/Purle 2022). The digital twin does not only connect the product with operations, but also connects the vendor with the customers and service partners. Also in this phase it is assumed that digital twins generate a high potential to increase competitive advantage and create value for the company. The data generated by simulations matched with knowledge about customer requirements lead to tailor-made sales arguments and offers.

Before a customer is willing to buy a product, machine or factory, it is important to show the dimensioning and demonstrate the functional capability. Customer interaction can be proven by means of virtual and augmented reality. Sales representatives equipped with these technologies are able to demonstrate the functionality, show the features and thus the product can be experienced by the potential customer. The buying behavior and buying decision can be affected positively and a competitive advantage can be created. Augmented reality can facilitate the work of the salesforce as information close to reality can be provided to the customers. Potential customers can look and feel in a very realistic way and this is more convincing as any advertisement or leaflet. The questions of the prospective buyers can be answered much faster and on a higher level of competence. The advice about features,

combination possibilities and compatibility to existing equipment or machinery can be substantiated immediately. Product configuration is easy to provide in the showroom and internet-based websites of the company or dealer organizations. Thus the buying decision will be executed on a more comprehensible way and customers see in advance and know exactly what they get.

As soon as the product is delivered or installed, the customer can use the product according to the specified requirements. The major concerns of the users are about convenience and reliability of the product. The manufacturer as the vendor has to take care that the requirements of the users are fulfilled. To meet the requirements of the users, a high volume of data is generated and has to be collected and analyzed during operation in order to monitor and optimize. The digital twin enables several assessments (Qi & Tao 2018, p. 3589): a) The real-time monitoring of the product in use collects all relevant data about workload, operating grade, usage status, environment data, process parameters, consumption data and degree of wear. Thus the operator is always up-to-date. b) On the basis of the collected monitoring data the virtual twin is able to simulate the operating behavior of the physical twin under different conditions. The outcome is the evaluation of the impact of different parameters and circumstances on performance, lifetime and consumption. Thus the operation of the physical product and even the emissions and waste can be optimized. c) Based on real-time data and historical data it is possible to predict the durability of products, future behavior and failures. In case the data are collected from one physical product, the digital twin is called Digital Twin Instance (DTI). In case that data are collected from more than one product of the same type, the virtual artefact is called Digital Twin Aggregate (DTA).

An additional advantage is that all collected data about performance and conditions of use are stored within the digital twin. These data have the potential to provide detailed information about product changes, upgrading, improvement and redevelopments.

4.4 Service

This phase belongs to the typical after sales phase and strives for failure-free utilization. In case of any disturbances, procedures of maintenance, repair and overhaul (MRO) have to be provided to keep downtime low (Hofbauer/Rau 2011, p. 90-103). Depending on the information gathered from collected data adequate reactions and precise recommendations are feasible. These actions can be executed immediately in case of emergency without any

delay or can be done in a proactive way. This means that in the predictive sense failures can be signaled in terms of kind, probability of occurrence, instant of time and extent. In the more sophisticated and prescriptive sense, recommendations to solve the problem are provided additionally. So it will be possible to provide tailored maintenance and service solutions to the manufacturer or customer. The digital twin collects, stores, analyses and compares all relevant incidents and causes and has immediate access to repair instructions and the table of wear parts and spare parts. All available data about failures, causes, maintenance instructions, operating parameters, current status and component quality have to be recorded and evaluated in order to provide efficient and detailed services to users (Tao et al. 2018, p. 3565).

At any stage of the PLM and this also applies here in the service phase, everything is dependent on the quality of the data. The accuracy of prediction and prescription rises with the volume of reliable data. By the means of preventive maintenance product failures are estimated to be reduced up to 70% and the potential of reducing cost of servicing is about 25% (Gebhardt 2017, S. 27).

Another important aspect in this phase is recycling and disposal. When the lifetime of a product ends the value of the product and especially the recirculation of valuable components should be considered. A huge potential can be assumed, when all relevant information about specification, status, fatigue fretting and maintenance history is available. These parts can precisely recirculated into the exact phase of the value chain in the sense of circular economy (Buchberger et al. 2019). Suitable strategies are repair, reuse or refurbish, before the product is going to be recycled. In the case of recycling there is a supplemental advantage (Reckter 2018, p. 1), when the twin exactly knows about material composition, material grade, substances and noxious matter. This helps to judge the resale value on the one side and prevents pollution and accidents on the other side.

The most important prerequisite however is to feed the digital twin from the very first beginning in the design phase with all the significant data.

It can be summarized that in any case the proper decision can be made without putting much time and effort in it. The resulting benefit is maximization of profit even at the end of product lifetime.

5 Challenges

This chapter comprises challenges of the utilization of the new technology of digital twins. As it is a new and promising technology, many companies are engaged in planning and preparation for applications of this new technology. But in most cases the management does not really know about the challenges and prerequisites and the potential of benefits.

There is an urgent need to explain the crucial prerequisites for successful implementation. Besides a well defined and stable product management process the data availability is the most crucial issue.

Current efforts of value creation in industry disclose obvious problems, which can be related to time, cost and quality. On the other side new and sometimes revolutionary technologies are introduced to overcome prevailing weaknesses and problems. Nowadays, in times of industry 4.0 and sensor-controlled processes, artificial intelligence (AI) and big data driven technologies are emerging. The big obstacle of using AI and big data in an integrated way is that the data are not available, not usable or limited, because most of the research is focused on physical products rather than on virtual objects. Further on, the use of big data is focused on selected single activities and not throughout all activities in an integrated way. Thus, the data use and data exchange are interrupted or even impossible whilst interoperability is missing.

Summing up, it can be summarized that the basic weakness in most of the industrial value chains is twofold: First, relevant information is missing or cannot be used for optimization due to lack of compatibility. Second, there is no stringent product management process implemented and related activities are not sufficiently integrated, neither in operations nor in terms of data exchange. Figure 10 displays the various steps of data management combining real and digital twin in order to optimize the product performance through the entire product management process.

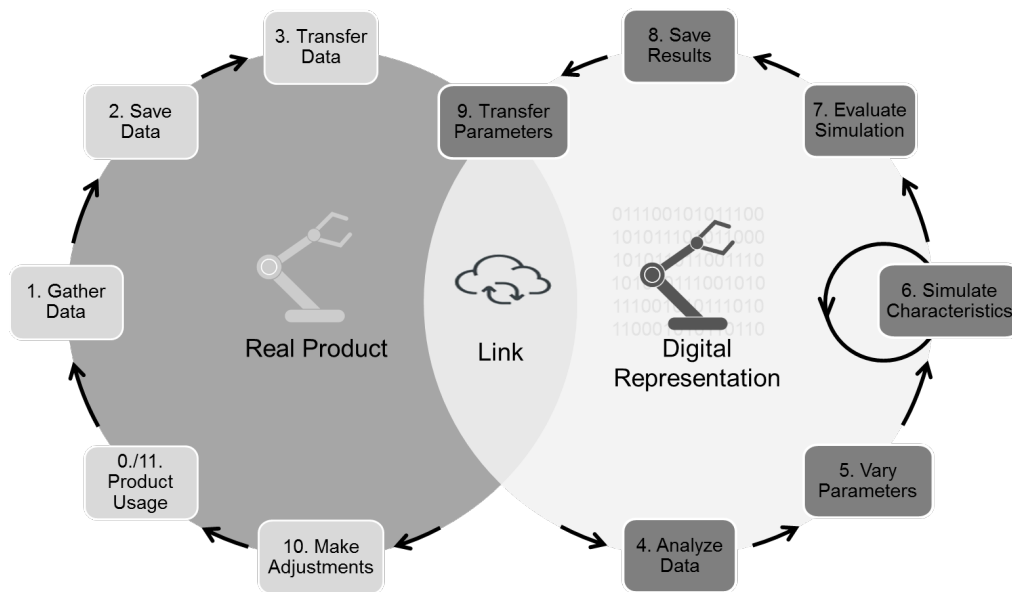


Fig. 10 Data usage for optimization around digital twins (Qi, Q. and Tao, F. 2018)

5.1 Data availability

Data availability is a severe topic for the usage of upcoming technologies. The problem of missing data and information can be solved by means of big data, cloud computing and artificial intelligence. Using big data implies to make dispositions to get the relevant information end-to-end to the right place in the right time. The digital data processing needs extensive data collection of all defined processes within their specific context. A failure detection has to assure that only data sets without faults will be used (Qi/Tao 2018). Once there is a valid set of data, this platform serves as an information desk. Thereby information is available about past and current conditions across all process steps. This platform also serves as the basis for the projection of future conditions.

The crux of the matter is that the essential input data are not available due to the missing communicative link between physical product and virtual model or there is no integration of data along the different phases over the product management process. This means that the data flow is interrupted, the data are segregated, uncomplete or incompatible and not useful to optimize the entire value chain. These problems truly imply suboptimal results in product management. The consequences are less transparency, less intelligence, less efficiency and less synergies (Tao et al. 2018, p. 3563).

In order to create a digital twin, a data base has to be established, where all the data from all the sources can be stored, before these data are screened, consolidated und further processed. The prerequisite condition is that the specification of the required data format, data selection and granularity of data is completed. This is the fundamental prerequisite of a real-time based assessment. The data collection will be executed for defined process parameters under respective conditions.

In the age of digital transition technological innovations provide manifold and powerful applications. There are three core aspects, which enable the realization of digitalization (WPG 2016, p. 24): 1) data availability, which describes the access to data, 2) data reliability, which describes the trustworthiness of the collected data and 3) last but not least the speed of processing for data transfer, data mining and analysis. The data management includes data acquisition and assessment of processes, quality attributes, products etc. as well as the respective environment. The digital twin introduces transparency to the processes and makes it easier to identify cause and effect. The overall goal is to optimize processes and quality and simultaneously save time and money.

On the basis of a digital twin questions like “Why did something happen?” can be answered in a first step. Conclusions about incidents in the past can be drawn with descriptive data analysis. In the next step questions like “What is happening?” can be answered with diagnostic analytics. The third step deals with predictive analytics and answers questions like “What will happen with what probability?” and in the fourth step optimization algorithms and simulation projections derive recommended actions in order to answer the question “What should be done?” to overcome a problem in a prescriptive way.

The necessity of big data approaches is given by rapid growth of collected data and database. To handle big data should not be an obstacle anymore. Big data is characterized by the 5-V model (Klein/Tran-Gia/Hartmann 2013), which means volume, velocity, variety, veracity and value. Volume describes how to handle large quantities of data. Velocity represents the accelerating speed of data processing. Variety stands for the multiplicity of formats and sources of data from collection, storage and analysis. Veracity addresses to reliability and value addresses to informational value. Figure 11 shows the dimensions of the 5-V model.

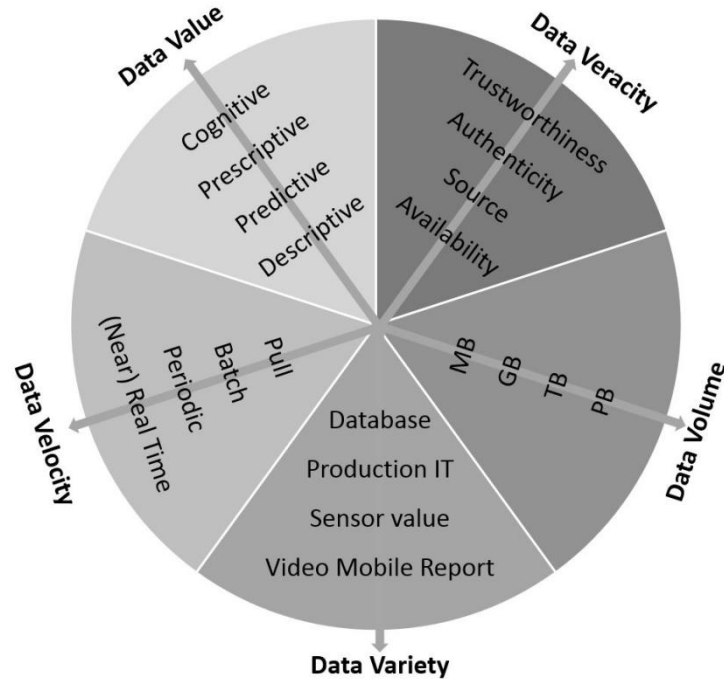


Fig. 11 Dimensions of the 5-V model for big data (Klein/Tran-Gia/Hartmann 2013)

Considering the outlined arguments of managing big data, this issue should not be an obstacle anymore.

5.2 Product management process

Product management takes care about the product from the very first idea through the whole life of a product until it will disappear from the market (Hofbauer/Sangl 2018). All related activities have to be executed in the most effective and efficient way to create competitive advantage and to earn profits. Value can be created by executing these activities better, faster and with lower cost expenditure than the competition.

The integration of all those activities in an interrelated process is essential to mine synergies and optimize the whole thing. The integration can be accomplished by installing clearly defined value creating activities, which are connected continuously without any interruption (Hofbauer/Sangl 2018, pp. 309-321). In doing this, the overall responsibility throughout the entire process will be ensured. The total set of activities concentrates on value creation of the entire value chain and not on single activities or sections. Another advantage can be stated in the reduction of mutual dependencies, interfaces and fractures.

The product management covers all required value-creating activities of a product from the beginning to the end of the product life (Hofbauer/Sangl 2018). According to a well-proven model, different process steps can be identified from the product concept until the lifecycle management (Hofbauer/Sangl 2018, p. 341). So far and for the reason of clarity the product management process (PMP) was displayed with 4 process phases (fig. 3). A more realistic, comprehensive and sophisticated PMP was developed by Hofbauer & Sangl (2018) consisting of 11 phases. Figure 12 displays the relevant process phases, which have to be analyzed in terms of applicability and benefits of digital twins.

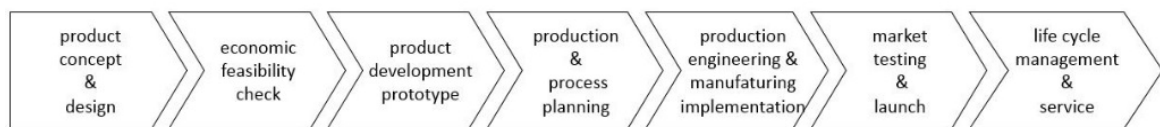


Fig. 12: Compound process activities in product management (own work)

Considering the proposed strict process orientation in organizing the value chain of product management, this issue should not be an obstacle anymore, too.

6 Example of Digital Twin Deployment in China

6.1 Preface

According to the international definition, digital twin is the integration of multi-disciplinary, multi-physical quantity, multi-scale, and multi-probability simulation processes using data from physical models, sensor updates, and operation history, and mapping them into virtual space to reflect the full life cycle process of the corresponding physical equipment. In short, digital twin aims to establish a digital counterpart model for real-world physical objects, and to dynamically simulate, monitor, analyze and control them through digital means. The concept originated from the industrial world, and with the development and wide application of new-generation information technologies such as 5G communication, Internet of Things, cloud computing, big data, artificial intelligence, etc., it has also been rapidly developed in China at both, the theoretical and application levels, extending to the fields of smart cities, smart parks, and smart transportation.

Intelligent forecasting and refined scheduling based on TCO (Total Cost of Ownership) are indispensable in mass production manufacturing. Facing the special requirements or temporary changes in customer delivery schedules, as well as possible sudden order skipping by suppliers, the traditional human scheduling model is obviously not enough to respond effectively, which may lead to chaos in the whole factory operation. A company tried to use outsourced APS software for scheduling in the past, but the effect has been poor. Based on the company's business practice, after the verification of intelligent scheduling in dozens of factories, they independently developed an intelligent scheduling system, combined with intelligent algorithmic models, and constructed an intelligent decision-making system, realizing the high efficiency and intelligence of supply chain operations. In the company's comprehensive digitalization and comprehensive intelligence strategy, Meiyun Intelligent Digital APS system has gradually built a more complete supply chain planning intelligent application scenario through continuous exploration and practice. In the multi-faceted practical application and testing, they have made significant progress in building a data-driven supply chain intelligent operation platform. By integrating resources to minimize the cost of the supply chain system and promoting efficient operation of the enterprise from the root, it realizes the complete APS+SCP from the supply chain sales forecast, S&OP to production scheduling and material planning of the whole process, thus realizing transparent and efficient production planning, on-time delivery of orders, improving the efficiency of production scheduling and supplier collaboration, and shortening the operation cycle of the supply chain plan.

6.2 Application of digital twins in the R&D process

6.2.1 Virtual Simulation Optimization Design Solution

A company uses digital twin technology to play a role in product design and optimization. Product design and validation are carried out in a virtual environment by creating a digital model that is identical to the physical product. Such digital models help engineers to better understand product structure and function so that potential problems can be identified and solved in the design phase, and improving product performance, quality and efficiency. Optimization of product structure, materials, and processes are performed in the digital twin model to improve product performance and reliability. Digital twin technology plays a role in a

company's R&D program management and process management. The digital twin platform enables systematic management of R&D projects, processes and simulations. Such a digital platform can help the company better manage R&D project progress, resource allocation and cost control, and improve the collaborative efficiency of the R&D process and the transparency of project management. The digital twin technology is used to simulate and optimize the process flow, improving the productivity and quality stability of products. With its own R&D and innovation advantages and accurate grasp of consumer market demand, a company constantly strengthens its digital hard power, established an integrated information management platform, including PLM, APS, SRM, ERP, MES, CRM, WMS and other operational systems, to achieve interoperability of R&D, supply chain, sales, finance, human resources and other business links. Meiyun Intelligent Digital provides digital solutions for user research, product planning, technical research and product development for this purpose, realizing accurate product planning, product collaborative integration, transparent project management and data-driven decision-making. In the context of end-to-end business and data content pull-through from global demand to product delivery, the two sides have established data flow and business flow rules for user demand library and product module library on the basis of product generalization and differentiation rules, built a full-process digital twin platform through CAD/CAE/CAM simulation technology, and introduced intelligent optimization into the R&D process, realizing a global platform group that takes advantage of R&D front-loading, testing front-loading, and manufacturing. It also introduces intelligent optimization into the R&D process, realizing a global platform group development mode with R&D front, testing front and manufacturing front as its advantages. Based on this, the two sides also introduced the self-developed GPM project management platform, DPM process management system and SDM simulation management platform, realizing the systematic management of R&D projects, processes and simulation. After the model was promoted, the new product mold change was reduced by 68%, the development cycle was shortened by 30%, and the revenue in 2021 was increased by more than 40% compared with 2018, and the digital and intellectual transformation and upgrading accelerated the innovation and development of the industry.

From 2017 to 2022, digitalization has penetrated into the corporate DNA, comprehensively improving the efficiency of production, supply, sales, research and other dimensions, promoting the transformation of the R&D mode from "single product" to "global platform group development" mode, We have realized the end-to-end and B2M customization

process, promoted the interconnection of internal and external user data, improved the accuracy and speed of product innovation, and the hit rate of planning has reached 70%, and the net recommendation value of user word-of-mouth (NPS) has reached more than 70%, and we have actively made the green commitment of "dual-carbon", and the completed dishwasher project has reduced the packaging materials by 30%. Reduced packaging materials by 30%.

6.2.2 MIoT.VC Digital Simulation Platform

A company uses digital twin technology to realize product modularization and generalization. Through the digital twin platform, it establishes the data flow and business flow rules of the user requirements library and the product module library to realize the optimized design of the product structure and components. Such a digital platform helps enterprises to better manage and utilize product module resources, realize modular design and generalized application of products, and thus improve the applicability and flexibility of products. A company utilizes digital twin technology to support the global platform cluster development model. Through the digital twin platform, it builds a full-process digital twin platform and imports intelligent optimization into the R&D process. Such a digital platform helps the company realize product development and co-design on a global scale, and improve the efficiency and quality of product design and development. Collaborative design and simulation analysis on the digital twin platform on a global scale speeds up the speed of product launch and the development of global markets.

Since 2012, a company has invested more than RMB 14 billion in digital transformation and incubated Meiyun Intelligent Digital to productize its own management practices in industrial scenarios such as digital consulting, intelligent manufacturing, digital R&D, digital marketing and services, and digital operation into software, and to provide intelligent manufacturing and industrial interconnection through big data, the Internet of Things, artificial intelligence, and cloud computing technologies with industrial software and SaaS services for smart manufacturing and industrial interconnectivity, to achieve China's smart manufacturing.

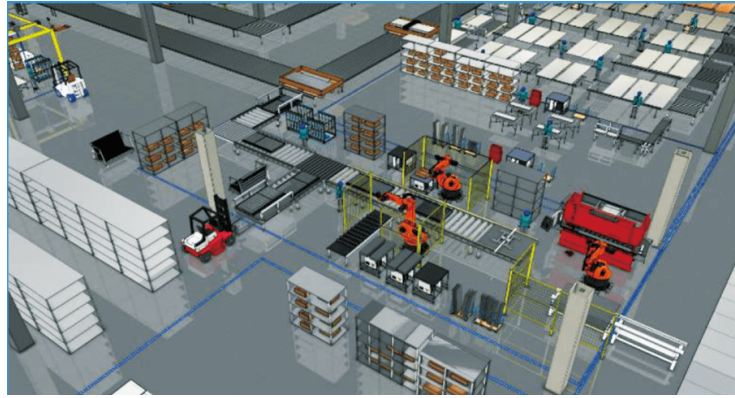


Fig. 13 MloT.VC digital simulation platform.

source: Midea Group appeared at the 8th China Robot Summit

As far as the industrial simulation field is concerned, a specific company is the industry leader. In 2017, a certain company acquired the internationally renowned industrial simulation company VC through its KUKA, and set up a domestic first-class industrial simulation research and development team with Meiyun Zhiyi Digital, and then launched the MloT.VC digital simulation platform (see in Figure(13) and Figure(14)).

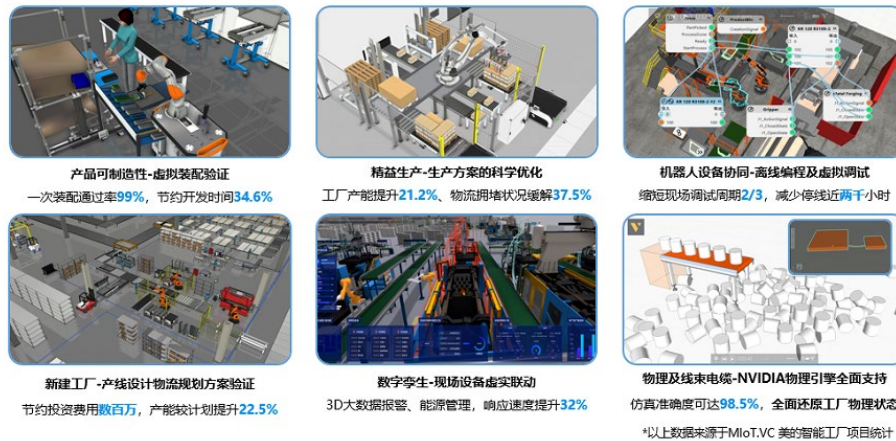


Fig 14 MloT.VC digital simulation platform.

Source: Midea "5 full 5 number" intelligent quality management model production and education integration activities

MloT.VC is one of the earliest industrial-grade digital simulation platforms in China, which accelerates product development, reduces investment costs, and comprehensively improves manufacturing efficiency by constructing a virtual digital factory. MloT.VC is a digital industrial

simulation platform that integrates 3D process simulation, assembly simulation, human-machine collaboration, logistics simulation, robotics simulation, virtual debugging, and digital twin factory. Platform VC can be applied to new factory production line layout design, logistics planning, value stream analysis; factory productivity improvement, lean improvement; new product development end of the manufacturability analysis, process design, assembly simulation; automation virtual debugging, robot trajectory planning and demonstration teaching and other scenarios.

6.3 Application of Digital Twins in Manufacturing Segments

6.3.1 Creating an Intelligent Digital Workshop

A company uses digital twin technology to achieve smart manufacturing and factory optimization (see fig. 15). Through the digital twin platform, it establishes a digital model that is exactly the same as the physical factory and combines with IoT, big data and artificial intelligence technologies to achieve real-time monitoring and optimization of the factory production process. Such a digital platform helps companies to improve production efficiency, reduce energy consumption and material waste, and achieve intelligent and sustainable development of the factory production process.

Manufacturing enterprises want to achieve leapfrog development, digital factory is the need to leap "Dragon Gate", and "Lighthouse Factory" as a benchmark, constantly rewrite the enterprise's business management, innovative production and competitive mechanism. The "Lighthouse Factory" has a great leading role in the transformation of the manufacturing industry, and with the help of the lighthouse digital factory construction, enterprises can also improve corporate profits, shorten the delivery cycle, improve capital turnover, increase cash flow and so on. The World Economic Forum mentioned that "Lighthouse Factories" utilize various advanced technologies to promote enterprise production and operation, and 66% of "Lighthouse factories" improve sustainability by reducing consumption, resource waste and carbon emissions; 82% of "Lighthouse factories" improve sustainability by reducing consumption, resource waste and carbon emissions; 82% of "lighthouse factories" improve sustainability by reducing consumption, resource waste and carbon emissions. 82% of "Lighthouse Factories" have improved productivity.

The vision of a company's lighthouse construction is to "horizontally" take the value stream as the main axis, build a group-level manufacturing center, pull through the value chain from marketing, R&D to manufacturing, and realize the interconnection of various process nodes, data perspective and early warning; "vertically" take the manufacturing cockpit, manufacturing sandbox/total control, DM Vertical" manufacturing cockpit, manufacturing sand table / total control, DM Kanban as a tool, combined with big data technology, to achieve the manufacturing system four-level comprehensive data management drive. Based on this, a company has built 5 lighthouse factories, and more and more "Lighthouse" value is emerging: 15 green factories, 3 zero-carbon factories.

In order to help other enterprises to increase confidence in digital transformation, a company quenched benchmark samples and summarized the lighthouse digital factory solution through the Meiyun Zhishu, bringing together the Meiyun Zhishu's national double-spanning platforms and ten years of digitization. Precipitation of industrial software, one of the world's leading manufacturers of industrial robots KUKA to provide from the single robot to the whole process of industrial automation, a hundred years of international leadership brand RISEGA deep plowing "one-stop" logistics automation, with "hardware, software, manufacturing knowledge with the advantage, RISEGA has exported the whole value chain of digital intelligent operation, production, operation and maintenance capabilities.



Fig 15 A company's digital intelligent factory.
source: Midea central air conditioning industry report

6.3.2 Digital Factory Facilitates Agile and Efficient Operations

A company uses digital twin technology to realize intelligent scheduling and production dispatching. By establishing a digital twin model, mapping the physical factory into virtual space, and combining real-time data updates and multidisciplinary simulation, real-time optimization and adjustment of production plans can be achieved. Such a digital platform can help companies better respond to order changes, production fluctuations and supply chain risks, and improve the accuracy and flexibility of production scheduling. Digital twin technology can also serve for quality control and predictive maintenance. Real-time monitoring and quality control of the production process can be realized through digital twin models and real-time data monitoring. Such a digital platform helps companies to identify and deal with quality problems in production in time, reducing product failure rates and production costs. At the same time, combined with big data analysis and artificial intelligence algorithms, it realizes predictive maintenance of equipment status and reduces production interruptions and maintenance costs caused by equipment failure.

A company's "lighthouse factory" (see fig. 16) -- a company's Kitchen Thermal Shunde factory, which is also the world's largest dishwasher production base, applies artificial intelligence, digital twins and other fourth industrial revolution technologies to the "end-to-end" value chain and other fourth industrial revolution technologies in the "end-to-end" value chain, reducing unit production cost by 24%, delivery time by 41%, R&D time by 30%, and defect rate by 51%. Meanwhile, hardware, self-developed industrial software and management software, together with 55 years of practical experience in the manufacturing industry, have formed such as the three generations, T+3, MBS, decentralized handbook and other practical wisdom. Through the application of digital technology to empower the entire manufacturing operation, together constitute the underlying pillars behind a company's lighthouse factory.



Fig 16. A Kitchen Thermal Shunde factory of a company.

source: Report on the construction of microwave electric appliance Industrial Park in Shunde by Midea Group

7 Conclusion

In summary the underlying hypothesis of this paper can be formulated that the potential benefit of digital transition is not fully exploited yet. The question of research is how the application of the digital twin can be employed to take advantage of that potential.

New technologies open strategic windows for innovative companies to create competitive advantages. The presented concept of the digital twin provides a very promising potential to optimize the entire process of value creation in the product lifecycle management (PLM). The digital twin enables smart PLM by combining the cyber and physical world by integrating all relevant data.

The potential benefits of using this revolutionary new technology are manifold. It can be stated that in each of the illustrated phases there is a huge potential to save time and money. Effectivity (to do the right things) as well as efficiency (to do the things right) can be fostered. In chapter 4 valuable advantages of the digital twin were presented for industry and customers as well throughout the whole lifetime of a product. A unique benefit of the digital twin is that data and data processing power is replacing the use and sometimes waste of physical resources like time, energy and material. Additionally, intelligence increases and cost decreases.

In chapter 6 the concrete deployment of digital twin technology was explained by examples from Chinese industry.

Figure 17 shows at a glance the different phases of application of the digital twin.

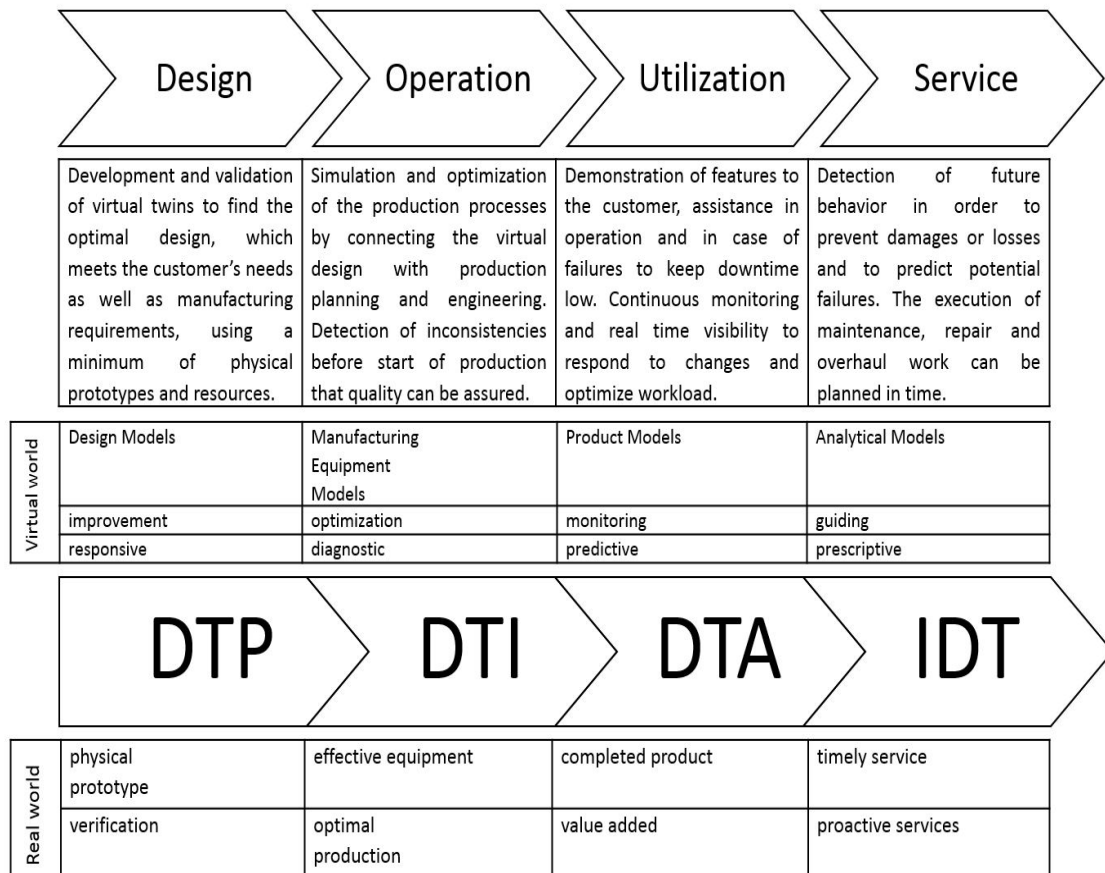


Fig. 17 Contextual recapitulation of real and virtual world interrelationship (own work)

There are different types of digital twins and the stage of maturation of the digital twin shall coincide with the purpose of application. In the early stage of PLM a basic version of digital twin may be satisfactory to decide about basic design concept. More sophisticated data processing and simulation models are necessary when the complexity and expectation during the advancement of realization is rising.

It can be outlined that competitive advantage increases through saving investment, reducing operational expenses, shortening time to market, reducing risks of faults and flops, raising performance and quality as well as increasing customer satisfaction and loyalty.

The benefit of this paper is the presentation of the conceptual framework of the digital twin along with a first consequent alignment with the PLM under consideration to identify

potentials of value creation. These potentials may become purpose of scientific discussion as well as targets for industrial implementation. But these potentials can only be overcome when the challenges of data management will be overcome. Appropriate big data management and artificial intelligence are promising approaches for smart applications.

Further research has to be done towards sustainability and circular economy.

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